Jurnal Kecerdasan Buatan dan Teknologi Informasi
Vol. 4, No. 3, September 2025, pp. 312-319
e-ISSN: 2964-2922, p-ISSN: 2963-6191
DOI : https://doi.org/10.69916/jkbti.v4i3.456

THE USE OF EXPLAINABLE AI FOR ANALYZING SOCIOECONOMIC DETERMINANTS OF THE HUMAN DEVELOPMENT INDEX IN INDONESIA BASED ON REGRESSION MODELS

Sintha Istikomah[1*], Dwi Purnomo Putro[2]

[1]Program Studi Sistem Informasi, Fakultas Ilmu Komputer, Universitas Safin Pati
[2]Program Studi Teknik Informatika, Fakultas Ilmu Komputer, Universitas Safin Pati
Email: [1]sintha_istikomah@usp.ac.id, [2]dwipp2019@gmail.com

(Received: July 29, 2025; Revised: September 12, 2025; Accepted: September 17, 2025)

Abstract

The Human Development Index (HDI) is a key indicator of quality of life, reflecting achievements in health, education, and a decent standard of living. Significant regional disparities in Indonesia highlight the need to analyze its determinants for effective policy formulation. This study examines the simultaneous influence of socioeconomic factors—poverty rate, GRDP per capita, life expectancy, mean years of schooling, and expenditure per capita—on HDI across 514 regencies/cities using machine learning and Explainable AI (XAI). Secondary data from the Indonesian Central Bureau of Statistics (BPS) in 2021 were utilized. The target variable (*IPM_score*) was constructed through feature engineering. Linear Regression, Random Forest, and XGBoost models were trained using an 80:20 split and evaluated with Mean Squared Error (MSE) and R^2. SHAP was applied to interpret feature contributions. Results show XGBoost achieved the best performance ($R^2 = 0.987$), outperforming Random Forest ($R^2 = 0.974$), while Linear Regression achieved $R^2 = 1.000$ due to perfect linearity. SHAP analysis identified expenditure per capita as the most dominant factor ($r = 0.9996$), followed by mean years of schooling ($r = 0.667$), while poverty showed a strong negative effect ($r = -0.638$). These findings emphasize that purchasing power and education are critical drivers of HDI. The use of XAI enhances model transparency and supports evidence-based policy, particularly in integrating poverty reduction with improvements in education and economic capacity.

Keywords: human development index, explainable ai, machine learning, xgboost, feature analysis.

1. INTRODUCTION

The Human Development Index (HDI) is an indicator that measures the achievement of quality of life based on three main dimensions: a long and healthy life, knowledge, and a decent standard of living [1]. Indonesia's HDI has shown a consistently positive trend, reaching 75.02 in 2024, an increase from 72.29 in 2021 [2]. However, behind this encouraging aggregate figure, there are substantial disparities across regions. The Special Capital Region of Jakarta (DKI Jakarta) recorded the highest average HDI_score in the 2021 dataset, while Papua ranked the lowest, reflecting longstanding structural inequalities in human development across Indonesia.

A comprehensive understanding of HDI determinants is a prerequisite for designing well-targeted policies. Previous studies in Indonesia have generally employed conventional econometric approaches, such as OLS regression or panel data models, to identify factors influencing HDI [3]–[5]. While these approaches are grounded in strong theoretical frameworks, their limitations in capturing nonlinear relationships and complex interactions among variables create opportunities for adopting more adaptive machine learning methods.

The era of big data and artificial intelligence has introduced a new paradigm in development analysis. Machine learning algorithms such as Random Forest and XGBoost (Extreme Gradient Boosting) have proven capable of capturing complex patterns in socio-economic data with predictive accuracy surpassing that of classical models [6]. However, the predictive superiority of these models often comes at the cost of interpretability, as they tend to function as "black boxes" that are difficult for policymakers to understand. This is where Explainable AI (XAI), particularly the SHAP (SHapley Additive exPlanations) method, plays a crucial role. SHAP provides consistent and fair numerical contribution values for each feature toward individual model predictions, based on cooperative game theory through Shapley values [7], [8]. The application of SHAP enables transparency in predictive models, thereby supporting evidence-based policymaking.

The integration of machine learning algorithms such as XGBoost with SHAP interpretation allows for more precise identification of determinant factors compared to classical econometric models [9]–[11]. By combining the strengths of panel data regression for controlling regional effects and machine learning for predictive accuracy, this study offers a holistic perspective on the architecture of human development in Indonesia over the past four years.

Numerous previous studies have explored HDI determinants using various approaches. At the international level, Ranis et al. [12] emphasized the bidirectional relationship between economic growth and human development: economic growth promotes HDI, while higher HDI accelerates growth. In Indonesia, similar findings have been reported in regional studies. Winarti [13] found that government expenditure in education and health sectors significantly affects HDI in Kalimantan. Meanwhile, Ruth Eugrina et al. [14] demonstrated that fiscal decentralization influences the quality of regional expenditure, which in turn impacts HDI at the regency/city level. These findings indicate that improvements in HDI result from complex interactions among macroeconomic factors, fiscal policies, and social conditions.

The limitations of conventional approaches in capturing such complexity have encouraged researchers to adopt machine learning methods. Isnan Prastiyo et al. [15] showed that Random Forest achieved the highest accuracy in predicting provincial poverty levels compared to other machine learning algorithms. On the other hand, the advancement of XAI methods has bridged the gap between predictive model complexity and the need for transparency in public policy. Mehrabi et al. [16] emphasized that algorithmic transparency is a prerequisite for stakeholder trust in AI-based systems within policy contexts. This gap between predictive capability and interpretability serves as the primary motivation for this study.

This research addresses the gap by integrating regression-based machine learning models (Linear Regression, Random Forest, and XGBoost) with XAI-SHAP interpretation to analyze the influence of socioeconomic factors on HDI across all regencies/cities in Indonesia based on 2021 data. The novel contributions of this study include: (1) the use of regression-based machine learning models for HDI prediction rather than merely correlation or OLS analysis; (2) the integration of SHAP for transparent feature contribution interpretation; and (3) a comparative analysis between classical models and tree-based models in the context of regional welfare prediction in Indonesia.

2. RESEARCH METHODS

This study follows a standard machine learning methodology, followed by result interpretation using XAI-SHAP. The overall research workflow is illustrated in Figure 1.

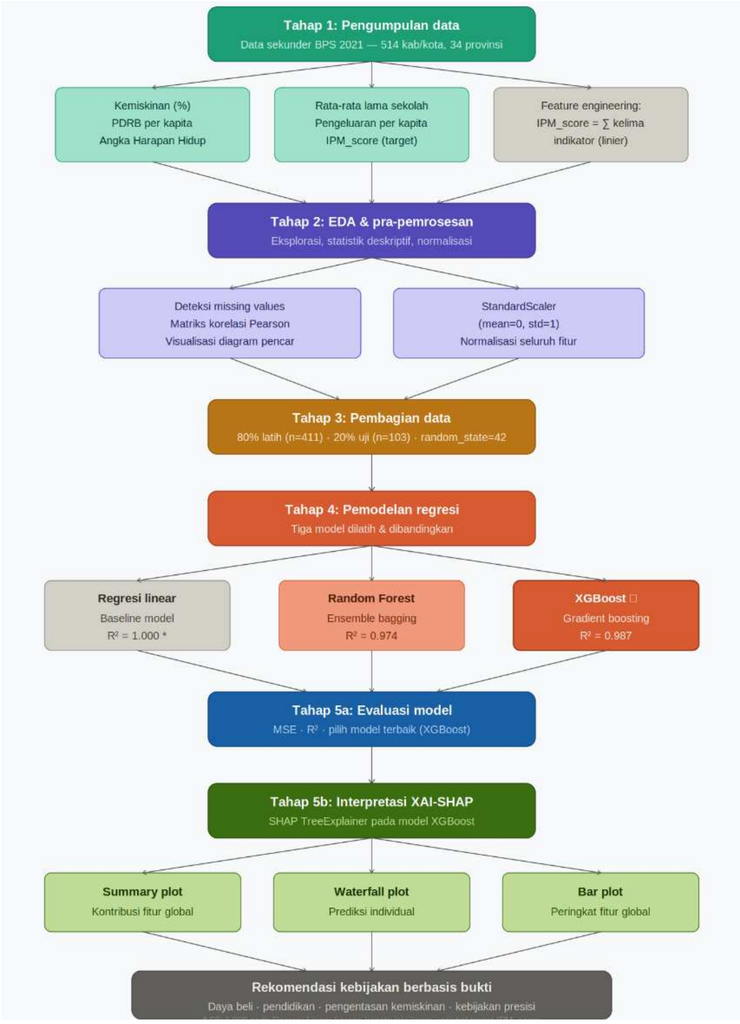

Figure 1. Research methodology workflow using a Machine Learning framework

2.1. Data and Variables

This study utilizes secondary data obtained from the Central Bureau of Statistics (BPS) of the Republic of Indonesia for the year 2021. The dataset covers 514 regencies/cities across 34 provinces throughout Indonesia. The selection of 2021 is based on the availability of comprehensive post–COVID-19 pandemic data, representing the early stage of national economic recovery. The variables used in this study are as follows:

Table 1. Operational Definition of Research Variables

Variable	Technical Name	Unit	Description
Percentage of Poor Population	*poorpeople_percentage*	%	Percentage of population living below the poverty line
GRDP per Capita	*reg_gdp*	Million IDR	Gross Regional Domestic Product per capita
Life Expectancy	*life_exp*	Years	Estimated average lifespan at birth
Mean Years of Schooling	*avg_schooltime*	Years	Average years of schooling for population aged 25+
Expenditure per Capita	*exp_percap*	Thousand IDR	Adjusted real expenditure per capita
HDI_score (Target)	*IPM_score*	–	Sum of the five features as the regression target variable

The target variable *IPM_score* was constructed through a linear combination of the five indicators as part of a feature engineering process, assuming equal contribution of each dimension in shaping regional welfare. The formulation is as follows:

$$IPM\_score = poorpeople\_percentage + reg\_gdp + life\_exp + avg\_schooltime + exp\_percap$$

2.2. Analysis Procedure

The analytical procedure in this study consists of five main stages:

The first stage is data exploration and preprocessing (EDA). At this stage, column name standardization, missing value detection, descriptive statistical analysis, and exploration of relationships among variables are conducted using the Pearson correlation matrix and scatter plot visualizations. All feature variables are then normalized using StandardScaler (mean = 0, standard deviation = 1) before being input into the models.

The second stage is data splitting. The dataset is randomly divided into training data (80%, n = 411 regencies/cities) and testing data (20%, n = 103 regencies/cities) using *random_state = 42* to ensure reproducibility.

The third stage is regression modeling. Three models are trained and compared: (1) Linear Regression as a baseline model; (2) Random Forest Regressor with default parameters from scikit-learn; and (3) XGBoost Regressor with default parameters. These models are selected to compare the performance of classical linear models with more flexible tree-based models.

The fourth stage is model evaluation using two metrics: Mean Squared Error (MSE), which measures the average squared difference between predicted and actual values, and the coefficient of determination (R^2), which measures the proportion of variance explained by the model. The model with the lowest MSE and highest R^2 on the testing data is selected as the best model.

The fifth stage is interpretation using SHAP. The SHAP TreeExplainer method is applied to the best-performing XGBoost model to compute SHAP values for each feature in the testing data. The resulting visualizations include: (a) SHAP summary plot for a global overview of feature contributions; (b) SHAP waterfall plot for individual prediction interpretation; and (c) SHAP bar plot for ranking global feature importance.

3. RESULTS

3.1. Statistik Deskriptif

The dataset used consists of 514 regencies/cities across 34 provinces in Indonesia. The descriptive statistics of the research variables are presented in Table 2 below.

Table 2. Descriptive Statistics of Research Variables (N = 514)

Variable	Min	Max	Mean	Std. Deviation	Median
Poverty (%)	2.38	41.66	12.27	7.46	10.46
GRDP per Capita (Million IDR)	1.04	819.00	34.80	84.16	13.07
Life Expectancy (Years)	55.37	77.86	69.62	3.46	69.92
Mean Years of Schooling (Years)	1.42	12.83	8.44	1.63	8.31
Expenditure per Capita (Thousand IDR)	3,976	23,888	10,324.79	2,717.14	10,196.50
HDI_score	4,071.24	24,622.00	10,449.92	2,744.67	10,300.89

Table 2 shows substantial variation in GRDP per capita, with values ranging from 1.04 million IDR (underdeveloped regions) to 819.00 million IDR (reflecting areas with very high economic activity such as industrial or mining regions). This wide range indicates extreme economic disparities across regions. The expenditure per capita variable exhibits a lower coefficient of variation, suggesting a relatively more even distribution of purchasing power, although significant variation still exists.

The poverty rate ranges from 2.38% to 41.66%, indicating that some regencies still face very high levels of poverty. Life expectancy spans from 55.37 years (regions with limited access to healthcare) to 77.86 years (regions with well-developed health infrastructure), while mean years of schooling vary from 1.42 years (very low) to 12.83 years.

3.2. Correlation Analysis

The Pearson correlation analysis between each feature variable and *IPM_score* is presented in Table 3. These results provide an initial empirical foundation prior to machine learning modeling.

Table 3. Pearson Correlation between Features and IPM_score

Feature Variable	**Correlation Coefficient (r)**	**Relationship Direction**	**Interpretation**
Expenditure per Capita	0.9996	Very Strong Positive	Dominant in determining *IPM_score*
Mean Years of Schooling	0.6668	Strong Positive	Education significantly affects HDI
Life Expectancy	0.5666	Moderate Positive	Health contributes positively
GRDP per Capita	0.3614	Weak–Moderate Positive	Economic factor has moderate influence
Poverty (%)	-0.6384	Strong Negative	Poverty significantly reduces HDI

The correlation between expenditure per capita and IPM_score ($r = 0.9996$) is the highest and nearly perfect. This is technically expected given the construction of IPM_score as a linear combination, in which expenditure per capita has a numerically dominant scale compared to other variables (with an average of 10,324, compared to an average poverty rate of 12.27 or mean years of schooling of 8.44). Strong positive correlations are also observed for mean years of schooling ($r = 0.667$) and life expectancy ($r = 0.567$), confirming the important roles of education and health dimensions in human development. In contrast, poverty shows a strong negative correlation ($r = -0.638$), indicating that regions with higher poverty levels tend to have lower HDI.

3.3. Machine Learning Model Performance

The evaluation results of the three regression models on the testing data (20% or 103 regencies/cities) are presented in Table 4.

Table 4. Comparison of Regression Model Performance on Testing Data

Model	**MSE (Test Data)**	**R^2 (Test Data)**	**Notes**
Linear Regression	≈ 0.00	1.000	Perfect R^2 due to *IPM_score* being a linear sum of features
Random Forest	259,264.58	0.974	Good performance, robust to outliers
XGBoost (Gradient Boosting)	127,950.96	0.987	Best model: lowest MSE, highest R^2 (excluding Linear Regression)

Linear Regression produces $R^2 = 1.000$ and MSE ≈ 0 because the target variable *IPM_score* is a perfect linear sum of all features—this condition allows linear regression to achieve mathematically perfect predictions. However, this also highlights a limitation in the construction of the target variable, which is overly deterministic. As a result, Linear Regression is not selected as the primary model for SHAP interpretation.

XGBoost demonstrates the best performance among tree-based models, with MSE = 127,950.96 and $R^2 = 0.987$, outperforming Random Forest (MSE = 259,264.58; $R^2 = 0.974$). This finding is consistent with the literature, which shows that XGBoost excels in structured tabular data. Its iterative boosting mechanism enables it to capture complex nonlinear interactions among variables that are not as effectively captured by Random Forest. Therefore, XGBoost is selected as the main model for SHAP analysis.

3.4. Feature Contribution Analysis

The SHAP analysis on the XGBoost model provides a quantitative overview of the contribution of each feature to the prediction of IPM_score. The ranking of features based on the mean absolute SHAP values is presented in Table 5.

Table 5. Feature Contribution Ranking Based on Mean |SHAP Value| (XGBoost)

Rank	**Feature**	**Mean |SHAP|**	**Dominant Direction**	**Policy Implication**
1	Expenditure per Capita (*exp_percap*)	Very High	Positive	Priority on improving household purchasing power
2	Mean Years of Schooling (*avg_schooltime*)	Moderate	Positive	Investment in quality education
3	Poverty (*poorpeople_percentage*)	Moderate	Negative	Integrated poverty alleviation programs

4	GRDP per Capita (*reg_gdp*)	Low–Moderate	Positive	Inclusive economic growth
5	Life Expectancy (*life_exp*)	Low	Positive	Improvement of basic healthcare services

The SHAP results confirm that expenditure per capita is the most dominant determinant in predicting *IPM_score*. High positive SHAP values indicate that higher real per capita expenditure in a region significantly contributes to increasing its HDI. This finding aligns with the argument that purchasing power directly reflects the ability of individuals to access healthcare, education, and other basic needs.

Mean years of schooling ranks second with positive SHAP values, indicating that investment in education—both in terms of access and quality—is a key driver of human development. Each additional year of schooling is associated with improvements in labor productivity and overall quality of life.

In contrast, poverty exhibits negative SHAP values, highlighting its role as a major constraint on human development. Regencies with higher poverty rates are consistently predicted by the XGBoost model to have lower HDI levels. This underscores that poverty alleviation is not merely a social agenda but a fundamental prerequisite for advancing human development.

GRDP per capita and life expectancy show relatively smaller SHAP contributions. For GRDP, this may be due to its strong correlation with expenditure per capita, as both represent overlapping economic dimensions within the model. The lower SHAP values for life expectancy may reflect its relatively more uniform distribution compared to economic variables, resulting in smaller interregional variation and thus a lesser impact on HDI predictions.

3.5. Spatial Analysis: Provincial HDI Patterns

To complement the model analysis, Table 6 presents the distribution of average IPM_score at the provincial level, identifying patterns of human development disparities across regions.

Table 6. Top Five and Bottom Five Provinces by Average IPM_score (2021)

Rank	Province	Average IPM_score	Key Characteristics
Highest 1	DKI Jakarta	19,078.40	National economic hub, highest per capita expenditure
Highest 2	Riau Islands	14,170.47	Advanced industrial and trade region
Highest 3	DI Yogyakarta	14,121.24	Education center, high mean years of schooling
Highest 4	Bali	13,815.95	Tourism sector drives per capita expenditure
Highest 5	Bangka Belitung	13,015.74	Active mining and industrial sectors
Lowest 1	Maluku	8,863.24	Limited infrastructure and service access
Lowest 2	North Maluku	8,043.72	Geographical fragmentation (archipelagic challenges)
Lowest 3	West Papua	8,039.47	High poverty, limited access to education
Lowest 4	East Nusa Tenggara	7,555.74	Uneven basic infrastructure
Lowest 5	Papua	6,926.54	Structural poverty and geographic isolation

The interprovincial disparity patterns shown in Table 6 reflect long-standing structural inequalities in Indonesia's development. Provinces with the highest HDI are generally economic growth centers with strong concentrations in services, industry, and education sectors. In contrast, provinces in eastern Indonesia—such as Papua, East Nusa Tenggara, and Maluku—face compounded challenges, including structural poverty and geographic fragmentation, which hinder equitable access to public services.

These findings highlight the importance of asymmetric policies that provide more intensive interventions for underdeveloped regions, rather than relying solely on uniform national policies. The SHAP analysis, which identifies per capita expenditure and education as dominant determinants of HDI, offers clear policy direction: programs aimed at improving purchasing power and expanding access to education in eastern Indonesia should be prioritized.

3.6. Discussion

a. Implications for Theory and Policy

Overall, the findings of this study confirm and reinforce previous research on the determinants of HDI in Indonesia, with the added value of quantitative precision provided by SHAP analysis.

First, the dominance of expenditure per capita in the SHAP analysis supports the view that human development is not solely determined by aggregate economic growth (GRDP), but rather by how such growth is translated into improvements in real purchasing power. This finding aligns with Sen's (1999) capability approach, which emphasizes that development is not merely about national income, but about individuals' ability to utilize resources to lead meaningful lives.

Second, the positive role of mean years of schooling reinforces the consensus that investment in education is the most effective long-term development strategy. Education not only enhances individual productivity but also strengthens people's ability to access and utilize healthcare services, creating a multiplier effect on HDI.

Third, the negative contribution of poverty underscores that non-inclusive economic growth—characterized by high poverty levels despite high GRDP—will not effectively improve HDI. Some resource-rich provinces in Indonesia exhibit relatively low HDI, reflecting the "resource curse" phenomenon, where natural resource wealth is not translated into human capital development.

Fourth, the application of XAI-SHAP introduces a level of transparency that is highly relevant for development governance. By identifying the specific contribution of each factor, local governments can implement "precision policies": identifying priority variables for intervention, allocating budgets more efficiently, and strengthening accountability in data-driven development planning.

b. Policy Recommendations

Based on the research findings, four priority policy recommendations are proposed:

First, strengthening household purchasing power through targeted cash transfer programs, productivity-based minimum wage policies, and the development of labor-intensive micro, small, and medium enterprises (MSMEs). Since per capita expenditure is the primary driver of HDI, policies that enhance real purchasing power will yield the most significant impact.

Second, accelerating improvements in the quality and accessibility of education, particularly in disadvantaged, frontier, and outermost (3T) regions. The mandated 20% education budget allocation in national and regional budgets should focus on improving teacher quality, school infrastructure, and scholarships for low-income populations, rather than merely increasing enrollment rates.

Third, implementing integrated poverty alleviation programs that combine economic interventions (such as business capital assistance and microcredit access) with social measures (such as healthcare coverage and educational scholarships). This holistic approach is more effective than fragmented sectoral programs.

Fourth, adopting data-driven "precision policy" approaches using XAI-SHAP at the regional level. Local governments can identify which variables require the most urgent intervention, enabling more efficient and accountable budget allocation.

c. Limitations and Future Research Directions

This study has several limitations. First, the target variable *IPM_score* is constructed as a simple sum of five indicators, which differs from the official HDI calculation method used by UNDP that involves normalization and geometric averaging. Second, the data used are limited to a single year (2021), which restricts the ability to capture temporal dynamics in human development.

Future research is recommended to: (1) use official HDI values from BPS as the target variable; (2) apply multi-year panel data for dynamic analysis; (3) incorporate additional variables such as income inequality (Gini index), healthcare infrastructure, and regional government expenditure; (4) explore other XAI methods such as LIME or Integrated Gradients for comparison; and (5) develop web-based applications that allow local governments to access SHAP-based analysis in real time.

4. CONCLUSION

This study successfully integrates machine learning and Explainable AI (XAI-SHAP) approaches to analyze the determinants of the Human Development Index (HDI) across 514 regencies/cities in Indonesia based on 2021 data. The findings indicate that the XGBoost model achieves the best predictive performance ($R^2 = 0.987$; MSE = 127,950.96) compared to Random Forest ($R^2 = 0.974$) and Linear Regression, which produces a perfect R^2 due to the linear construction of the target variable. Both correlation and SHAP analyses consistently identify expenditure per capita as the most dominant determinant of HDI ($r = 0.9996$; highest SHAP value), followed by mean years of schooling ($r = 0.667$) as the second most important positive factor. In contrast, the percentage of the poor population shows a significant negative contribution to HDI ($r = -0.638$; negative SHAP values), confirming poverty as a major barrier to human development that must be addressed systematically. Furthermore, substantial spatial disparities are observed, with western provinces such as DKI Jakarta, Riau Islands, and DI Yogyakarta dominating the highest HDI levels, while Papua, East Nusa Tenggara, and Maluku remain at the lowest ranks. Finally, the integration of SHAP successfully transforms machine learning models from "black boxes" into transparent and interpretable tools, making them highly relevant for evidence-based policymaking.

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